A Framework for Analysing System Intelligence of the Building Control System: A Study of the Integrated Building Management System

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Abstract

The lack of satisfactory consensus for characterizing the system intelligence and structured analytical decision models has inhibited the developers and practitioners to understand and configure optimum intelligent building systems in a fully informed manner. So far, little research has been conducted in this aspect. This research is designed to identify the key intelligent indicators, and develop analytical models for computing the system intelligence score of smart building system in the intelligent building. The integrated building management system (IBMS) was used as an illustrative example to present a framework. The models presented in this study applied the system intelligence theory, and the conceptual analytical framework. A total of 16 key intelligent indicators were first identified from a general survey. Then, two multi-criteria decision making (MCDM) approaches, the analytic hierarchy process (AHP) and analytic network process (ANP), were employed to develop the system intelligence analytical models. Top intelligence indicators of IBMS include: self-diagnostic of operation deviations; adaptive limiting control algorithm; and, year-round time schedule performance. The developed conceptual framework was then transformed to the practical model. The effectiveness of the practical model was evaluated by means of expert validation. The main contribution of this research is to promote understanding of the intelligent indicators, and to set the foundation for a systemic framework that provide developers and building stakeholders a consolidated inclusive tool for the system intelligence evaluation of the proposed components design configurations.

1. Introduction

Few would dispute that the intelligent building has become a prevailing form of building development over the past decade or so, and that this trend has been particularly notable in Asia. The desire for an effective and supportive environment within which an organisation can reduce energy consumption, improve worker productivity, and promote maximum profitability for their own business has stimulated the growth of highly adaptable and responsive buildings (Clements-Croome, 2001a). Recent years have seen a variety of intelligent building control products developed and introduced to the market, designed to enhance building 'intelligence' performance and environmental sustainability, and to satisfy a variety of human needs. The adjective "intelligent" has been extensively applied to portray the smart properties of the building system products. Manufacturers of intelligent technologies often claim their systems are more intelligent than others of their kind, but these assertions tend to be vague and unjustified (Bien et al., 2002). It leads to a concern about the abuse of the term 'intelligent' without making any effort to clarify what the 'intelligent' building control system should be (Park et al., 2001; and Schreiner, 2000).

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Over the last two decades, building intelligence has been increasingly perceived by developers as a unique and important measure to reflect the specific performance and properties of intelligent buildings, however little has been known on the assessment of the system intelligence of building control systems. The perspectives and understandings of 'intelligence' are also still so abstract and ambiguous. Although some closely related studies in machine intelligence measurement have been documented in engineering literature over the past decade (Szu, 2000; Park et al., 2001; Bien et al., 1998 and 2002), there is a dearth of research investigating the degree of intelligence of building control systems in intelligent building and construction literature (Wong et al., 2008a). The aim of this research is to identify the key intelligent indicators, and develop analytical models for computing the *system intelligence score* of smart building system in the intelligent building. In this study, the integrated building management system (IBMS) was used as an illustrative example to present a framework. The survey conducted in this study aims to provide suggestions on the required features needed to advance the state-of-practice in building control systems. The specific objectives of this research are to perform the following:

- To formulate general theoretical framework that incorporate the 'suitable' intelligence attributes and indicators for evaluating and assessing the degree of system intelligence of IBMS;
- To refine the conceptual model, and to test the level of importance of the intelligence indicators via an approach combining the Analytic Hierarchy Process (AHP) and the Analytic Network Process (ANP);
- To develop practical model of intelligence performance analysis, and to validate and check the robustness of the practical model.

2. A Review of Machine Intelligence Theory

Bien et al. (1998 and 2002) developed a revised Machine Intelligence Quotient (MIQ) for the measurement of the machine IQ. The model generally includes four key attributes of machine intelligence which were identified from a vast review of intelligent control system literature. These four key intelligence attributes are (1) autonomy (AUT); (2) man-machine interaction (MMI); (3) controllability of complicated dynamics (CCD); and, (4) bio-inspired behaviour (BIB). According to Bien et al. (2002), autonomy refers to the abilities of performing self-operative functions, including self-calibration, self-diagnostics, fault-tolerance and self-tuning. Man-machine features include ergonomic design, emergence of artificial emotion, and human-like understanding or communication. The key features or indicators of controllability for complicated dynamic systems are considered to be non-conventional model-based, adaptation, non-linearity, and motion planning under uncertainty (Bien et al., 2002). The bio-inspired behaviour relates to the system's capability of performing bio-inspired behavioural traits, and the system's ability to interact with the building environment and the services provided. An intelligent system should exhibit a number of bio-inspired traits: biologically motivated behaviour, cognitive-based behaviour, and characteristics of neuroscience (Bien et al., 2002). To sum up, the theory of machine intelligence by Bien et al. (2002) assumes that an intelligent machine or system should be autonomous, be capable of man-machine interaction, exhibit bio-inspired behaved, and possess the ability to control complicated dynamics. The model further posits that any intelligent system with the four identified intelligence attributes can generally lead to improved safety, enhanced reliability, higher efficiency, and more economical maintenance.

In this study, the model of machine intelligence by Bien et al. (2002) is extended to investigate and evaluate the degree of system intelligence of the IBMS system. The proposed model in this research differs somewhat from that suggested by Bien et al. (2002) in that the interrelationships between the intelligence attributes of the building control systems and the operational benefits of the intelligent building are taken into consideration. This is based on the argument that the adoption of intelligent technologies in buildings should not be limited to advances in technology, as the abilities of the installed intelligent control systems to enhance the goals or benefits of the clients and end-users are equally significant (Clements-Croome, 2001b; and, Smith, 2002). The model of Bien et al. (2002) is extended to consider the relationship between the degree of intelligence possessed by the intelligent building control system and the extent of the expected benefits/goals achieved (Wong et al., 2008a and 2008b). In specific, investigating their relationships is based on the assumption that the intelligence attribute(s) of the IBMS will be most important when in achieving the decision maker's goal of improved operational benefits. In contrast, each of the four key intelligence attributes previously mentioned (i.e. autonomous features) might have a varied degree of importance in generating four identified operational benefits. The four key operational benefits of intelligent building include 'improved operational effectiveness and energy efficiency', 'enhanced cost effectiveness', 'increased user comfort and productivity', and 'improved safety and reliability' (Wong et al., 2008a and 2008b).

3. Research Methodology

To test the conceptual model, two successive surveys were undertaken. A general questionnaire was first used to elicit and identify the 'suitable' intelligence indicators. Mean scores of each proposed CSC were calculated, and the t-test analysis was used to determine the importance level of the intelligence indicators. It should be noted that it was not expected a large sample size of professionals and experts were obtained, as the intelligent building is a new form of building development which is yet to mature. Then, a more subjective multi-criteria decision making (MCDM) approach, a method of combining the Analytic Hierarchy Process (AHP) and the Analytic Network Process (ANP) was purposely conducted to prioritise the intelligence indicators, and to investigate the influences of interrelationships between the intelligence attributes and the operational benefits of the intelligent building on their relative importance (Wong et al., 2008b). The AHP, a decision making theory developed by Thomas L. Saaty in 1980, is aimed at handling a large number of decision factors and providing a systematic procedure for ranking many decision variables (Tang et al., 2004). The AHP is a structural approach which assists in eliciting preference opinions from decision makers, allowing both qualitative and quantitative approaches to solve complex decision problems. It then 'combines' them into a single empirical inquiry (Cheng and Li, 2002). ANP is an advanced version of the AHP which models a network structure that relaxes the hierarchical and unidirectional assumption in the AHP. The ANP can provide a more generalised model of multi-criteria decision-making that takes interdependent relationships into consideration (Cheng *et al.*, 2005). An AHP-ANP questionnaire will be designed for this purpose. The results of the two surveys were used to develop and refine the conceptual intelligence analytic model.

In order to evaluate the feasibility and applicability of the developed conceptual model, two process steps were developed to transform the developed conceptual model from experimental/ theoretical framework formulation to the practical model (Leeflang et al., 2000). These two steps include: (1) the development of rating scales and assessment methods of evaluating each building control system candidate against its relevant intelligence indicators; and, (2) the establishment of a score aggregation formula to produce one overall score for each of the candidate building control systems.

Model validation was conducted to check the robustness of the practical models and to examine whether they could simulate the decision of the experienced intelligent building experts. The model validation design in this study was based on the approach of Ling et al. (2003) to test the selection model for design consultants for design-and-build projects by consulting a number of experts. In this study, in order to evaluate the candidate IBMS against each intelligence indicator in the model developed, the assessment methods and standard summated rating scales must first be set up for each of these intelligence indicators. Having established the assessment methods and rating scores for each intelligence indicator, the scores of intelligence indicators are then aggregated in order to produce one overall score for each candidate IBMS. To derive the weighted rating or scores, the important weights of each intelligence indicator are multiplied by the ratings that the candidate IBMS obtains for the corresponding intelligence indicator. The validation exercises first required the experts to nominate two alternatives for the IBMS they had encountered in their past experience. They were told to evaluate the nominated IBMS alternatives based on their expert judgement and on their global impression of them. Each proposed building system alternative was first ranked according the experts' preferences for them. The experts were then requested to use the practical system intelligence analytic model to evaluate the nominated building system alternative. The results will compare the aggregate scores in both models and test whether they are consistent with the preferences of the experts for both parts. Scores of system alternative given by the model and judged by the experts were further examined in their similarities by correlation analysis. The Pearson correlation coefficient (*r*) and the Spearmen rank order correlation coefficient (*rho*) are employed to ascertain the strength and direction of the relationship between the scores of models and experts. If there is a high correlation between the two sets of scores, this means that the model is able to reflect the expert's preference

4. Establishment of System Intelligence Analytical Model

4.1 Development of Key Intelligence Indicators

The first general survey is designed to elicit the 'suitable' intelligence indicators for the IBMS. The list of proposed intelligence indicators was derived from an extensive review of intelligent building literature and trade publications, and expanded on with the advice of industry experts and practitioners. The posited intelligence indicators were developed and organised into four main intelligence attributes suggested by Bien *et al*. (2002). To examine the suitability and comprehensibility of the questionnaire, a pilot study was first undertaken. In the main survey, a total of 157 questionnaires were sent out and distributed, and 44 usable replies were collected for the analysis, giving a net usable response rate of 28%.

In the survey, participants were invited to elicit their opinions on the suitability of each of the proposed intelligence indicators on a 5-point Likert-scale format (1= Not suitable; 2= Less suitable; 3= Suitable; 4= More suitable; and, 5= Most suitable). The critical rating was fixed at scale '3' since ratings above '3' represent 'suitable', 'more suitable' and 'most suitable' according to the scale. Mean score ratings and *t*-test analysis were employed as the statistical techniques to elicit and analyse the 'suitable' intelligence indicators. In this survey, the selection of the specific person to elicit their opinion is based on their experience and knowledge of intelligent building. A survey invitation letter was first prepared and addressed to the executives or directors of all targeted companies via postage or, in a few cases, e-mail. The invitation letter attempted to confirm which companies had real practical experience in intelligent building design and development, and to obtain approval and pre-agreement for participation in the surveys. Only those professionals in the companies with relevant experience are included in this study. To maximise the survey sample size, the 'snowball' sampling approach is adopted to ask the directors or executives of the targeted companies for the referrals to additional intelligent building experts or practitioners that they knew (Creswell, 2002). Table 1 tabulates the results of the first general survey, a total of 16 critical system intelligence indicators for the IBMS.

4.2 Refining the Conceptual Analytical Model by the AHP-ANP Methods

A more meticulous investigation and prioritisation of the 'suitable' intelligence indicators was then conducted to obtain a penetrating insight of the measurement of the degree of system intelligence in IBMS. In this survey, the influence of the interdependent relationship between intelligence attributes of the IBMS and the operational benefits of intelligent buildings was taken into consideration. A combination of the AHP and ANP methods was utilised to execute the prioritisation of indicators. Detail of ANP algorithm procedure was described in Saaty (1996), Meade and Sarkis (1998) and Cheng et al. (2005).

- **Development of conceptual analytical framework:** A hierarchical decision network for the decision problem to be evaluated was first established based on the general survey results. At the top of the control hierarchy is the ultimate objective (Level 1), which is to determine the overall degree of system intelligence of the IBMS. The top level is broken down into intelligence attributes (Level 2) and their corresponding intelligence indicators (Level 3). In order to investigate the interdependent relationships between intelligence attributes and operational benefits, another separate but related component, relating to the building's operational benefits, is depicted above the intelligence attributes in the decision model. Four operational benefits act as external variables and form network relationships with the four intelligence attributes in the analytical decision model.
- **Establishment of matrices:** A total of 9 experts participated in the AHP-ANP survey. A questionnaire was designed to pair-wise compare the matrices of interdependent component levels and variables of intelligence attributes. The estimation of the relative importance of the two compared elements follows the relative importance weight of interdependence was also determined by using a 9-point priority scale of pair-wise judgement which was developed by Saaty (1996). The four intelligence attributes (Level 2) of IBMS in this study were rated pair-by-pair with respect to the decision problem (Level 1). Then, the relative importance of the intelligence attributes (e.g. autonomy vs. man-machine interaction) with respect to a specific operational benefit of the intelligent building was investigated. A pair-wise comparison matrix was required for each of the operational benefits for calculation of impacts of each of the intelligence attribute.
- **Calculation of local priority:** The relative importance of each intelligence indicator with respect to each of their corresponding intelligence attributes was investigated. The final evaluation was conducted by averaging of all expert respondents as it was assumed that the importance (i.e., knowledge, expertise, and perceptions) of all experts were equal. In the case of any unequal allocations of importance, a weighted average is used (Sarkis and Sundarraj, 2002: 342). In this survey, all completed pair-wise comparisons by the respondents appeared to have acceptable consistency. The local priority weights (LPW) for the relative importance of the benefits on the intelligence attributes were then investigated. As a result, the weighted priorities for each of intelligence attributes were combined to form a four column, four row matrix.

- **Formation and analysis of the super-matrix:** The super-matrix promotes a resolution of the effects of the interdependence that exists between the elements of the ANP model. This can be achieved by entering the local priority vectors (LPV) in the super-matrix, which in turn obtains the 'global' priority vectors (GPV). The final sub-step of the ANP calculation relates to the calculation of a limit super-matrix by the *Super Decisions*. Details of AHP-ANP evaluation process are discussed in Wong et al. (2008b). The results of the average limiting super-matrix with final weights of each intelligence indicator of IBMS were summarised in the second column of Table 2.

Table 1: A Summary of 16 Key System Intelligence Indicators for the IBMS

Intelligence Indicators	Attribute Group
• Adaptive limiting control algorithm (AL)	Group 1
• Self-diagnostic of operation deviations (SD)	Group 1
• Year-round time schedule operation (YT)	Group 1
• Ability to link multiple standalone building control systems from a variety of manufacturers (ALMS)	Group 2
• Remote control via internet (RCI)	Group 2
• Ability to connect multiple locations (ACML)	Group 2
• Alarms and events statistics (AES)	Group 2
• Control/ monitor lighting time schedule/zoning (ML)	Group 2
• Control and monitor HVAC equipments (MHVAC)	Group 2
• Reports generation and output of statistical and trend profiling of controls and operations (RG)	Group 3
• Ability to provide operational & analytical functions (APOAF)	Group 3
• Single operation system/ platform for multiple location supervision (SOS)	Group 3
• Graphical representation and real-time interactive operation action icons (GR)	Group 3
• Run continually with minimal human supervision (RC)	Group 3
• Analyse operation function parameters (AOF)	Group 4
• Provide adaptive control algorithms based on seasonal changes (PAC)	Group 4

Note: Group 1= autonomy; Group 2 = controllability for complicated dynamics; Group 3 = man-machine interaction; and, Group 4 = bio-inspired behaviour

The findings of the AHP-ANP survey suggested that, in the IBMS, the top three intelligence indicators – *'self-diagnostic of operation deviations'; 'adaptive limiting control algorithm';* and, *'year-round time schedule performance'* – are all under the attribute of 'autonomy'. This indicates that an 'intelligent' IBMS should possess the capability of detecting the deviations in its operation and self-adjusting these problems.

5. Model Application and Validation

5.1 Application of the Model

The primary step was to identify rating scales and to establish assessment methods for each of the intelligence indicators. The summated rating scales, which ranged from 0 to 5, were adopted (Ling, et al., 2003). Eight rating methods were established and verified by two industry experts who participated in the ANP survey. Details of rating methods are specified in Wong (2007). Having established the assessment methods and scoring systems, the next process step required for performing system intelligence analysis was to aggregate the scores to produce one overall score for the IBMS. The score for each intelligence indicator is obtained by multiplying the weights (*w*) of each intelligence indicator with the ratings (*r*) that each proposed building system obtained for the corresponding indicators. All individual scores of the intelligence indicators under the same building control system are then summed up to produce an aggregate system intelligence score. In this case, the mathematical expression for the aggregate system intelligence score, named *System Intelligence Score* ($Score_{SI}$), is given as follows:

$$Score_{SI} = (\sum w_{II1} \times r_{II1}) + (\sum w_{II2} \times r_{II2}) + (\sum w_{II3} \times r_{II3})... + (\sum w_{IIn} \times r_{IIn}) \quad \text{(Eq.1)}$$

where, $w_{II1}, w_{II2}, w_{II3...}w_{IIn}$ represent the weights of the intelligence indicators; and, $r_{II1}, r_{II2}, r_{II3...}r_{IIn}$ represent the rating given to the IBMS option for the intelligence indicators.

In this paper, two real IBMS candidates (i.e. System 1, and System 2) were selected for demonstrating their assessment procedures and computation of the *System Intelligence Score ($Score_{SI}$)*. The brand names were all fictitious, and the product information was undisclosed in this paper to prevent any commercial conflicts. A score from 0 to 5 was assigned to each intelligence indicator. Table 2 summarised the judgements of the expert on the intelligent performance of Systems 1 and 2. In this example, although the Aggregate *System Intelligence Score ($Score_{SI}$)* of man-machine interaction (MMI) was higher in System 2, System 1 had higher aggregate scores in another two intelligence attributes: autonomy (AUT) and controllability for complicated dynamics (CCD). Finally, the demonstration results indicated that System 1 (3.8351) had a higher aggregate system intelligence score than System 2 (3.6333).

Table 2: Aggregate System Intelligence Score ($Score_{SI}$) of Two IBMS Candidates

Intelligence Indicators (Attribute Group*)	Indicator's weight - ANP	IBMS System 1		IBMS System 2	
		Score	Weight	Score	Weight
AL (Group 1)	0.0916	4	0.3664	3	0.2748
SD (Group 1)	0.0926	4	0.3704	4	0.3704
YT (Group 1)	0.0822	4	0.3288	3	0.2466
ALMS(Group 2)	0.0464	4	0.1856	4	0.1856
RCI(Group 2)	0.0280	5	0.1400	4	0.1120
ACML (Group 2)	0.0363	4	0.1452	4	0.1452
AES(Group 2)	0.0657	5	0.3285	3	0.1971
MHVAC(Group 2)	0.0677	4	0.2708	4	0.2708
ML(Group 2)	0.0565	4	0.2260	3	0.1695
RG(Group 3)	0.0276	3	0.0828	5	0.1380
APOAF(Group 3)	0.0386	3	0.1158	4	0.1544
SOS(Group 3)	0.0436	4	0.1744	5	0.2180
GR(Group 3)	0.0505	4	0.2020	5	0.2525
RC(Group 3)	0.0803	4	0.3212	4	0.3212
AOF(Group 4)	0.0896	3	0.2688	3	0.2688
PAC(Group 4)	0.1028	3	0.3084	3	0.3084
	Weighted Mean ($Score_{SI}$) =		3.8351		3.6333

Note: Intelligence indicators weights were normalised. The indicators were rated based on a scale of 0-5 based on their existence and level of functions/services. Maximum score of SIS = 5.0000.
*Group 1= autonomy; Group 2 = controllability for complicated dynamics; Group 3 = man-machine interaction; and, Group 4 = bio-inspired behaviour

5.2 Model Validation

A group of 5 intelligent building experts were then invited to validate the system intelligence analytic models. The relative rankings of the different alternatives of IBMS were first compared with the order of preference from the experts. Then, the study verified how similar the experts' and models' scores were. A model validation questionnaire was designed to obtain information from the experts about their opinions and judgements of the system intelligence of the candidate IBMS. Each expert was invited to supply and nominate two candidates for IBMS. Then, the experts were invited to indicate a preference for each pair of IBMS they nominated. A score from 0 to 10 (i.e., 0 to 4 represent 'poor'; 5 represents 'average'; 6 and 7 represent 'good'; 8 represents 'very good'; and, 9 and 10 represent 'excellent') were again assigned for each alternative based on their overall intelligent performance or degree of intelligence (Ling et al., 2003). Then, the experts were invited to evaluate the same set of alternatives by using the system intelligent analytic model as described in Table 3. A weighting score between 0 (extremely poor) and 5 (excellent) based on the assessment methods were assigned to reflect the degree of each of the nominated IBMSs in fulfilling each intelligence indicator. Table 3 summarises the experts' global preference scores and models' aggregate scores of each candidate IBMS. The results indicate that 80% (i.e. 4 out of 5) of the models' aggregate scores orders are in the same way as the experts' preference.

Table 3: Summary of Experts' and Model's Scores

Expert	Proposed IBMS options	Models' aggregate scores (Ranking of scores)	Experts' global score (Ranking of scores)
MVEX1	MVEX1-IBMS1	4.2074 (1)	8 (1)
	MVEX1-IBMS2	3.7100 (2)	7 (2)
MVEX2	MVEX2-IBMS1	3.6098 (2)	6 (2)
	MVEX2-IBMS2	3.9534 (1)	7 (1)
MVEX3	MVEX3-IBMS1	3.7852 (1)	8 (1)
	MVEX3-IBMS2	3.4866 (2)	7 (2)
MVEX4	MVEX4-IBMS1	4.0176 (1)	9 (1)
	MVEX4-IBMS2	3.6403 (2)	7 (2)
MVEX5	MVEX5-IBMS1	4.0575 (2)	9 *
	MVEX5-IBMS2	4.2664 (1)	9 *

Note: * Same score was assigned by the expert on the overall ability or performance of the control system

In addition, the model's aggregate scores (column 3 of Table 3) were further correlated with the expert global scores (column 4 of Table 3). The results of the Pearson correlation coefficient (r) and Spearman's rho between the models' aggregated scores and the experts' global scores for each IBMS were calculated. The analysis results indicate a high correlation between all experts' scores and the scores generated by the models with respect to the degree of intelligence. The value of Spearman's rho is 0.820, while the value of Pearson's r is 0.771. This implies a 'very strong' relationship between the experts' and models' system intelligence scores of the IBMS in general (de Vaus, 2002).

6. Conclusion

The approach adopted in the current paper has generated some interesting findings, however, it should be noted that this approach has proved to be excessively time-consuming and complex. The current study is limited to domestic (i.e. Hong Kong) intelligent building development. Also, the perspective on the nature of control systems elicited by the experts or professional in this study would possibly be bound by their existing conception and practice of what constitutes a control system, and therefore a wider audience and subject matter should be selected in the further study. Future study should also include the building occupants as part of the survey sample because they are the end-users of the intelligent building. Similar empirical work of this study can be extended and further developed in other countries, for other building control systems, or in other types of intelligent building. Some new variables may be added into the model. A larger sample would help for improving the extent to which these models represent human decision making processes. The application of software and group decision support systems, on the other hand, can minimise the difficulties in implementing this technique. To conclude, as the intelligent building technologies continuously evolve and develop into the foreseen future, system intelligence analysis of the building control systems will continuously be seen as an area of interest to explore and investigate.

This study presents the development of indicators, and develops analytical decision models for appraising system intelligence of the IBMS. The findings of the AHP-ANP survey suggested that 'self-diagnostic of operation deviations', 'adaptive limiting control algorithm', and 'year-round time schedule performance' are the three top intelligence indicators of the IBMS. This indicates that an 'intelligent' IBMS should possess the capability of 'autonomy' including detecting the deviations in its operation and self-adjusting these problems. The System Intelligence Score can be viewed as a reference for existing buildings as well as future developments to systematically analyse the intelligence performance of specific building systems which value to the modern building. This survey conducted in this study provided suggestion the required features needed to advance the state-of-practice in building control systems, and also demonstrated the application of ANP as a tool to quantify the system intelligence of the smart building systems.

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